

TO Interested Parties  
FROM Global Strategy Group on behalf of Democratic Governors Association  
DATE May 17, 2019  
RE Overview of the DGA Late Movement Model

This memo outlines the DGA's work over the last three years to develop a Late Movement Model to better understand and predict late shifts in the electorate leading up to election day. In other words, a model that helps us predict where undecided voters are going to end up, and which voters are likely to defect from their stated choice in pre-election surveys. The model allows the DGA to adjust pre-election survey topline to get a more accurate assessment of how the race is likely to look on Election Day based on projected late movement. It also allows the DGA to better target individuals who have a higher chance of defecting or breaking at the end of a campaign. Below, we review how this project came to be, how we have continued to build out and develop this model every cycle, and our most recent results.

## **Origination**

This project was born out of the surprising results of the 2015 governor's race in Kentucky. That year, the polling done by the Jack Conway campaign and the DGA IE, as well as public polling and, as we found out later, internal Republican polling all showed Jack Conway with a small but stable lead with about a week to go before Election Day. As we know, Matt Bevin ended up winning the race by about 9 points.

In order to understand this apparent industry-wide polling miss, we quickly rushed into the field with a post-election panel survey where we re-contacted respondents of the campaign and IE's pre-election polls and asked how they voted. This survey showed that the polling wasn't inaccurate, but rather that there had been significant movement in the last week to 10 days with pre-election undecideds breaking overwhelmingly for Bevin and a significant number of Conway voters also defecting to the Republican.

## **2016: Rural/Red States**

In 2016, we took the first steps in a multi-year investigation to better understand late movement. Across four states – Missouri, Indiana, West Virginia, and Montana – we conducted pre- and post-election polling to understand what voter file data and survey questions, when asked before the election, were likely to predict late movement among undecideds or late defection from either the Democratic or Republican (or third party) candidates. For example, as shown below, whether a voter had ever considered voting for another candidate was an important predictor of defection. Based on these results, we then built a statistical model to predict the likelihood of each respondent in a survey to defect from their stated pre-election candidate and the likely direction that late deciders would break based on voter file variables and responses to questions on pre-election surveys.

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One of the best leading indicators of support shifts was whether a respondent admitted that they would consider voting for other candidate

#### Chance Vote for Opposing Party



#### 2017: Virginia

In 2017, we deployed this model, using it to adjust pre-election survey topline in Virginia to provide an estimate of the likely vote on Election Day. The model proved to be effective, taking pre-elections survey data at three different points during the campaign that showed Ralph Northam with leads of anywhere from two to five points and predicting that late movement would boost that margin up to a 7 to 11-point range – very close to the final actual results of a 9-point victory.

		Topline Vote	Model-Adjusted Vote	Actual Vote
<b>Wave One</b> Sept. 20-28, 2017	Northam	43%	53%	54%
	Gillespie	41%	46%	45%
	Hyra	3%	1%	1%
	Undecided	13%		
	Margin	1.5%	6.9%	8.9%
<b>Wave Two</b> Oct. 18-22, 2017	Northam	47%	54%	54%
	Gillespie	42%	45%	45%
	Hyra	3%	1%	1%
	Undecided	8%		
	Margin	5.0%	9.9%	8.9%
<b>Wave Three</b> Oct. 30 – Nov. 6, 2017	Northam	48%	55%	54%
	Gillespie	43%	44%	45%
	Hyra	2%	1%	1%
	Undecided	6%		
	Margin	4.7%	10.9%	8.9%

## 2018: A Diverse Mix

In 2018, we then updated the model with our data collected in Virginia in 2017 and deployed it across several races. It again proved to be a value add, adjusting polling topline numbers to predict Election Day margins that ended up being closer to the actual results in states like Georgia, Nevada, Ohio, Oregon, Maine and New Mexico (for instance, in Georgia, polling in September and early October showed Stacey Abrams with a 6-point lead, but when the model adjusted these topline numbers, it predicted just a 1-point lead, much closer to the eventual margin of -1). Unlike in 2017, we did not engage in any pre-election polling as part of this specific project, rather the topline numbers represent the final topline numbers from each campaign.

	Topline Margin	Model-Adjusted Margin	Actual Margin
Georgia	+6	+1	-1
Nevada	+1	+4	+4
Ohio	-8	-3	-4
Oregon	+1	+4	+6
Maine	+3	+6	+8
New Mexico	+6	+8	+14

The graph below demonstrates how the shift occurred in Oregon, where the model predicted that late breakers would inflate Kate Brown's margin from 1 to 4 points (close to her actual 6-point win). Our post-election survey in the state showed that Brown held on to her supporters better than Republican Knute Buehler would and that she won slightly more voters who were undecided or indicated that they would vote 3<sup>rd</sup>-party on pre-election surveys.

### Oregon: Brown was more successful holding onto her support as well as winning third party and undecided voters

